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ECONOMIC EFFICIENCY OF WIDESPREAD USE OF ARTIFICIAL INTELLIGENCE IN INDUSTRIAL ENTERPRISES IN THE CONTEXT OF THE UZBEK ECONOMY

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Abstract. This article analyzes the economic efficiency of implementing artificial intelligence (AI) technologies in Uzbekistan's industrial sectors. The main applications considered include process optimization, predictive maintenance, quality control, supply chain management, energy management, and occupational safety. Key performance indicators such as ROI, NPV, TCO, OEE, and TFP are proposed to assess efficiency. In addition, a practical "roadmap" and regulatory-organizational recommendations tailored to Uzbekistan's conditions are provided. Investment-return factors are systematically explained through calculations and scenario examples.

Keywords: artificial intelligence, Industry 4.0, predictive maintenance, OEE, ROI, TCO, supply chain, Uzbek industry, energy efficiency, digital transformation.

Introduction. Industrial sectors in Uzbekistan—including energy, oil and gas, chemical, textile, mechanical engineering, and building materials—contribute significantly to the country's GDP. In recent years, digital transformation programs, automation in production, and the need for data-driven decision-making have gained momentum. Artificial intelligence (AI)—including machine learning, deep learning, computer vision, natural language processing, and optimization algorithms—offers great potential to improve productivity, reduce costs, and enhance quality in industrial enterprises.

The purpose of this article is to systematically evaluate the expected economic efficiency of widespread AI adoption in industry under Uzbek conditions, highlight the main application areas, propose financial and economic performance indicators, and provide a practical roadmap.

Theoretical and Methodological Basis

- **Production function and efficiency:** Traditionally, production volume YYY is expressed in terms of capital KKK and labor LLL, while technological factors are incorporated as an ordered coefficient:

$$Y = A \cdot K\alpha \cdot L^{(1-\alpha)}$$

The implementation of AI provides an additional growth source through **A** (technological efficiency) and practically through **K**, the composition of digital assets (sensors, ERP systems, automated process control systems, cloud computing, and models).

- Contribution to overall production efficiency:

$$\Delta \ln Y \approx \alpha\, \Delta \ln K + (1-\alpha)\, \Delta \ln L + \Delta \ln A$$

In many cases, the effect of AI is reflected through Δln A\Delta \ln AΔlnA; in a simplified form, it can be estimated as: $\Delta \ln A = \beta \, \Delta \ln AI + \varepsilon$

Efficiency:

Overall equipment effectiveness (OEE) is expressed as the product of its main components:

OEE = Availability × Performance × Quality

AI improves all three factors by predicting failures in advance and optimizing operational parameters.

Main Application Areas of AI in Uzbek Industry:

- Predictive Maintenance:
Using vibration, temperature, and current/pressure sensor data, neural networks or gradient models predict the probable time of failure.
Expected benefits: Reduction of unplanned downtime by 20–40%; optimization of spare parts turnover.
- Quality Control (Computer Vision):
Real-time detection of defects (e.g., textile fiber flaws, microcracks in metal structures).
Benefits: Reduced losses, fewer customer claims, and automated inspections.
- Supply Chain and Demand Forecasting:
Time series and hybrid models are used to predict demand, delivery times, and risks related to currency/raw material prices.
Benefits: Optimal inventory reduction by 10–25%; decreased logistics costs.
- Energy Management:
Optimization of load profiles and energy mix; reduction of consumption during peak hours; automated optimization of compressors, furnaces, and pumps.
Benefits: Energy consumption reduced by 5–15%.
- Occupational Safety and Environmental Monitoring:
Detection of hazardous situations using cameras and sensors; monitoring of gas emissions.
- Digital Twins and Process Optimization:
Simulation aimed at KPI targets; parameter selection using Reinforcement Learning.
- Finance and Asset Portfolio Management:
Modeled budgeting; optimal capital repair based on asset life cycle.

Performance Assessment Indicators and Formulas:

- Return on Investment (ROI):

- Inline expression: for quick estimation, ROI can be calculated as

$$\mathrm{ROI} = \frac{\mathrm{CostsBenefits}}{\mathrm{Costs}}$$

Net Present Value (NPV):

$$\mathrm{NPV} = \sum_{t-0}^{T} \frac{B^t - C^t}{(1+r)^t}$$

- (B^t) — Annual benefit (e.g., reduced downtime, energy savings, reduced defects)
- (C^t) — Costs (licenses, infrastructure, personnel)

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- (r) — Discount rate

Total Cost of Ownership (TCO):
The sum of all costs over the project lifecycle, including equipment, cloud, data storage, cybersecurity, and personnel training.

OEE Growth Example:
If initial (OEE_0 = 60%) and AI implementation increases it to 72%, the real increase in production capacity is 20%.

Technological Efficiency (TFP) Estimates:

$$\Delta TFP \approx \Delta \ln A \approx \beta \Delta \ln AI$$

In practice, (\beta) ranges from 0.05–0.20 depending on the sector; thus, a 10% increase in AI assets can increase TFP by 0.5–2%.

Illustrative Scenario – Textile Factory Example:

- Baseline: Monthly production value 10 billion UZS, (OEE = 60%), unplanned downtime 30 hours/month, defect rate 4%
- AI package: Computer vision + predictive maintenance + energy optimization
- Costs: CAPEX 2.5 billion UZS (sensors, cameras, servers/cloud, integration), OPEX 0.5 billion UZS/year (licenses, infrastructure, model service)
- Expected impact:
  - Downtime −40% → additional work ≈12 hours/month → +1.2 billion UZS/year
  - Defects 4%→2% → savings ≈ 2% × 10 billion × 12 = 2.4 billion UZS/year
  - Energy −8% (energy costs = 15% of total) → savings ≈ 0.15 × 10 billion × 12 × 0.08 = 1.44 billion UZS/year
- Total annual benefit: (B_1 \approx 5.04) billion UZS
- Simplified ROI (Year 1): $ROI = \frac{5.04-(2.5+0.5}{(2.5+0.5)} = \frac{2.04}{3.0} = 68\%$
- In practice, ROI may grow over 12–24 months; for NPV, a discount rate (e.g., (r = 20%)) and a 3–5 year horizon are recommended.

Sector-Specific Potential in Uzbekistan:

- Energy & Oil & Gas: Predictive maintenance for pump/compressor stations; demand forecasting and load balancing to reduce losses.
- Chemical & Fertilizer: Reactor parameter optimization, safety monitoring, computer vision for product granulometry.
- Textiles: Defect detection in fiber, dyeing, and stitching; demand forecasting; cutting optimization.
- Mechanical Engineering & Metallurgy: CNC trajectory optimization, tool wear prediction, cognitive inspection.
- Construction Materials (cement/brick): Furnace optimization, fuel consumption reduction, waste monitoring.

- Agro-Industry (industrialized supply chains): Synchronization of deliveries, cold chain monitoring.

Risks and Constraints:

- Data quality & infrastructure: Low sensor coverage reduces model reliability; standardized tags and SCADA/MES/ERP integration required.
- Personnel capabilities: Shortage of data engineers, MLOps, automation specialists; corporate upskilling needed.
- Cybersecurity: Strong OT/IT protection, network segmentation, IAM, monitoring.
- Ethics & Legal: Personal data privacy, video analytics, algorithmic fairness, IP issues.
- MLOps: Versioning, monitoring, drift, retraining cycles.

Practical Implementation Roadmap:

- 0–3 months: Business case and KPIs (OEE, defects, energy, downtime), data audit, pilot selection (1–2 lines).
- 4–9 months: Sensorization and integration with SCADA/MES/ERP; pilot models (predictive maintenance, visual inspection, A/B or shadow mode); cybersecurity architecture.
- 10–18 months: Scale pilots from line → workshop → plant; MLOps (CI/CD, monitoring, drift control, auto-releases); personnel training (technologists, mechanics, energy specialists, AI analysts).
- 18–36 months: Full-scale investment: infrastructure, digital twins; additional initiatives: supply chain optimization, semi-autonomous control loops; KPI recalibration and economic evaluation.

Governance and Regulatory Recommendations:

- **Data Governance:** Data catalog, tagging standards, retention policy, classification of personal/industrial data.
- **Standards Compliance:** ISA-95, OPC UA, ISO 27001 / 62443 alignment.
- **Localization & Import Substitution:** Open architecture solutions, avoid vendor lock-in.
- **State Support:** Grants/tax incentives, testbeds, industrial coworking, training academies.
- **Measurement & Audit:** Independent OEE/energy audits, algorithmic audit, risk assessment.

Economic Modeling and Metrics:

- **Project Portfolio Prioritization:**
  - Quick wins: low cost, high impact (visual inspection, energy anomaly detection)
  - Strategic projects: digital twins, supply chain optimization
- **Cascaded KPIs:**
  - Production: ΔOEE, WIP, throughput
  - Quality: FPY, PPM, claims
  - Energy: kWh/unit, peak load, carbon footprint

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  - Finance: ROI, NPV, Payback, TCO
- **Sensitivity Analysis:** Adjust key assumptions ±10–20% to test NPV stability.
- **National Context:** Include electricity prices, exchange rates, logistics factors.

Conclusion:
Widespread adoption of AI in Uzbek industrial enterprises is economically viable: significant reduction of downtime, defect reduction, energy savings, and supply chain optimization ensure high returns. Efficiency depends on sensor coverage, data quality, personnel capabilities, and MLOps discipline. Systematic application of ROI/NPV/TCO and OEE/TFP metrics is recommended. Public-private collaboration, standardization, and workforce development enable rapid and sustainable scaling of AI solutions.

References for Implementation:

- International consulting reports: McKinsey, BCG, Deloitte – industrial efficiency case studies.
- Economic efficiency and TFP: textbooks and articles on production functions and technological growth.
- Standards: ISA-95, OPC UA, ISO 27001, IEC 62443.
- Energy management: practical guides on industrial energy audits and optimization.
- MLOps: technical publications on deploying, monitoring, and managing model drift.

Appendix – Practical Checklist:

- **Data:** Sensor map, completeness, frequency, calibration.
- **Integration:** SCADA/MES/ERP connectors, APIs, research environment.
- **Models:** Business objectives, metrics (AUC, F1, MAE), validation.
- **Execution:** Operator interface, incident management, change control.
- **Security:** Network segmentation, audit logs, backup/DR.
- **Management:** Implementation schedule, responsible persons, budget, KPI reporting.

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